Opportunistic Resource Scheduling for Wireless Ad-hoc Networks*

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Abstract

In this paper, we present a joint power scheduling and rate control scheme for wireless ad-hoc networks. Compared with wireline networks, a unique characteristic of wireless networks is that the channel condition is time-varying. By appropriately exploiting the variation of the channel condition at each link, one can more efficiently utilize wireless resources resulting in higher system capacity or less consumption of resources. We model the time-varying wireless channel as a stochastic process and formulate a stochastic optimization problem, which aims at maximizing system efficiency by controlling the power allocation of each link and the data rate of each user in the system. The joint power scheduling and rate control algorithm is obtained by using stochastic duality and implemented via stochastic subgradient techniques.

1 Introduction

In contrast to traditional wireless cellular networks in which communication is achieved between the (fixed) access point and (mobile) nodes by using single-hop transmissions, in wireless ad-hoc networks, communication is typically achieved between (mobile) nodes by using multi-hop transmissions. Hence, ad-hoc networks have a substantially different structure from cellular systems and network control schemes for one system is not applicable for the other. In fact, the structure of ad-hoc networks is, in some ways, similar to that of wireline networks such as the Internet. They are highly decentralized and use multi-hop transmissions for communication. However, there also exist fundamental differences between them. In contrast to wireline networks where each node is fixed and each link has a fixed and independent capacity, in ad-hoc networks, each node might be moving and each link has time-varying capacity (dependent on the channel condition) that might be dependent on other links. Due to these differences, network control schemes for wireline networks also cannot be directly applied to wireless ad-hoc networks. Thus, there are a real need and a tremendous interest in studying various problems related to wireless ad-hoc networks, such as routing, power control, and rate control [5, 3, 4, 17, 16, 1, 19, 11].

One of the important lessons that we have learned from the study of (cellular) wireless networks is that by appropriately exploiting the time-varying wireless channel, we can more efficiently utilize radio resources, e.g., increase system performance and decrease the consumption of resources. Hence, there has been a great deal of effort on the development of "opportunistic scheduling" and power control schemes taking into account these variations in the channel condition [13, 12, 14, 2, 8, 15, 10, 9]. The basic idea of "opportunistic scheduling" is allocating resources to links when they experience good channel conditions while avoiding allocating resources to links when they experience bad channel conditions, thus efficiently utilizing radio resources. In such works, the authors model the variation of the channel condition of each wireless link as a stochastic process and develop optimal scheduling algorithms that maximize system performance and satisfy some fairness or performance constraint of each user while opportunistically exploiting the stochastic nature of the channel condition. They show that opportunistic scheduling schemes provide higher system performance than non-opportunistic schemes that do not exploit the variation of the wireless channel.

However, even though it is well known that resource allocation taking into account the variation of the wireless channel condition is important for system efficiency, there has been little work on the subject for wireless ad-hoc (multi-hop) networks. Opportunistic scheduling schemes in [13, 12, 14, 2, 8, 15, 10, 9] have been developed only for cellular (single-hop) networks. In [5, 3, 4, 17, 1, 19, 11], resource allocation schemes in ad-hoc networks have been developed assuming the channel condition of each link is con-

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stant. In [16], a joint power allocation and routing scheme has been developed for time-varying ad-hoc networks. This scheme stabilizes the network, if the input data rates are within the capacity region. However, it may not provide the optimal solution in terms of network efficiency (e.g., maximizing network throughput and minimizing power consumption), which is important in wireless networks due to the increasing demand on wireless services, the scarcity of radio resources, and the finite battery life-time of each node in the system.

In this paper, we study a joint opportunistic power scheduling and rate control problem in wireless ad-hoc networks by considering the time-varying channel condition at each link. We formulate an optimization problem that aims at maximizing network efficiency, which is defined as the weighted sum of the utilities of all users and power consumption of all nodes in the system, with constraints on the data rate of each user and the power consumption at each node. By solving this problem, we develop a joint opportunistic power scheduling and rate control algorithm in which each user adjusts its data rate based on feedback from the system and each node allocates transmission power to each link that emanates from it considering the demand on rate allocation and the channel condition of the link.

The rest of the paper is organized as follows. In Section 2, we describe the system model considered in this paper and formulate the optimization problem. In Section 3, we present the joint opportunistic power scheduling and rate control algorithm. Numerical results are provided in Section 4. Finally, we conclude in Section 5.

2 System model and Problem

We consider a wireless ad-hoc network that consists of a set of nodes $\mathbf{N}$ and a set of links $\mathbf{L}$. We denote a link from the transmitter at node i to the receiver at node j as (i, j) and a set of links that emanate from node i as $\mathbf{L}_i^{out}$. Note that a link is an abstract representation of communication between two nodes. There are a set of users $\mathbf{M}$ in the network and each user m has its fixed routing path for communication. We denote a set of links that user m is using for its communication as $\mathbf{V}_m$ and a set of users that are using link (i, j) as $\mathbf{M}_{i,j}$. Each user m has a utility function $U_m(x_m)$, where x_m is its data rate. We assume that U_m is a continuous and strictly concave function of x_m.

We consider a synchronous time-slotted TDMA/CDMA system where a unique orthogonal code is assigned to each link for communication [1]. Hence, there is no interference between transmissions at different links. Each node i has a maximum transmission power level P_i^T and in each time-slot it determines its transmission power level and data rate for each link in $\mathbf{L}_i^{out}$. We allow the channel condition of each link to vary across time-slots and model it as a stationary stochastic process. In a time-slot, the system is assumed to be in one of several possible states, in which each state represents one of several possible levels of channel conditions for all links. Each state takes a value from a finite[1] set $\mathbf{S}$. We denote the probability that the system is in state s as π_s.

We define the signal to noise ratio (SNR) of each link (i, j), $\gamma_{i,j}^s$ when the system is in state s as

$$\gamma_{i,j}^s(P_{i,j}^s) \quad = \quad \frac{G_{i,j}^s P_{i,j}^s}{n_j^s}, \tag{1}$$

where

$P_{i,j}^s$**:** power allocation for link (i, j) when the system is in state s,

$G_{i,j}^s$**:** path gain from node i to node j when the system is in state s,

n_j^s**:** background noise at node j when the system is in state s.

As in [3, 4], we assume that the data rate that can be achieved is a linear function of the SNR. The data rate $r_{i,j}^s$ for link (i, j) when the system is in state s is thus defined as

$$r_{i,j}^s(P_{i,j}^s) \quad = \quad W\gamma_{i,j}^s(P_{i,j}^s), \tag{2}$$

where W is the bandwidth of the system.

We use a weighted sum of the utilities of all users and the average power consumption of all nodes as a measure of system efficiency. The system efficiency is defined as

$$F(\bar{x}, \bar{P}) = \sum_{m \in \mathbf{M}} a_m U_m(x_m) - \sum_{s \in \mathbf{S}} \pi_s \sum_{i,j:(i,j) \in \mathbf{L}} b_{i,j} P_{i,j}^s, \tag{3}$$

where a_m and $b_{i,j}$ are non-negative constants, $\bar{x} = (x_m)_{m \in \mathbf{M}}$, and $\bar{P} = (P_{i,j}^s)_{i,j:(i,j)\in\mathbf{L},\, s\in\mathbf{S}}$. Then, the optimization problem that we study in this paper is formulated as:

$$\text{(P)} \qquad \max_{\bar{x}, \bar{P}} F(\bar{x}, \bar{P})$$
$$\text{s. t.}$$
$$\begin{aligned}
& x_m^{min} \le x_m \le x_m^{max}, && m \in \mathbf{M}, \\
& \sum_{s \in \mathbf{S}} \pi_s r_{i,j}^s(P_{i,j}^s) \ge \sum_{k \in \mathbf{M}_{i,j}} x_k, && (i,j) \in \mathbf{L}, \\
& \sum_{s \in \mathbf{S}} \pi_s \sum_{j:(i,j) \in \mathbf{L}_i^{out}} P_{i,j}^s \le P_i^a, && i \in \mathbf{N}, \\
& \bar{P}_i^s \in \mathbf{P}_i^s, && i \in \mathbf{N},\ s \in \mathbf{S},
\end{aligned}$$

where x_m^{min} and x_m^{max} are minimum and maximum data rates for user m, P_i^a is the maximum average power

[1]Note that this assumption is not restrictive, since in a real system, the channel condition of a link is mapped into a level set with a finite number of levels by using quantization.

consumption of node i, $\bar{P}_i^s = (P_{i,j}^s)_{j:(i,j)\in\mathbf{L}_i^{out}}$, $\mathbf{P}_i^s = \{(P_{i,j}^s)_{j:(i,j)\in\mathbf{L}_i^{out}} \mid \sum_{j:(i,j)\in\mathbf{L}_i^{out}} P_{i,j}^s \le P_i^T,\ 0 \le P_{i,j}^s \le P_i^T,\ \forall j:(i,j)\in\mathbf{L}_i^{out}\}$, and P_i^T is the maximum transmission power limit of node i. Hence, by solving this problem, we can obtain joint power scheduling and rate allocation that maximizes the system efficiency under constraints on the minimum and maximum data rates of each user (i.e., the first constraint), the capacity of each link (i.e., the second constraint), and the average power consumption and the maximum transmission power limit of each node (i.e., the third and fourth constraints).

In the next section, we will develop the algorithm that solves problem (P). The first question that arises before solving this problem, is how to ensure feasibility, i.e., how do we ensure that there exists a power scheduling and rate control policy that satisfies the constraints. This can be achieved by adopting an appropriate call admission control strategy. The development of such a strategy is outside the scope of this paper. Instead, in this paper, we assume that the system has an admission control policy in place that ensures feasibility and focus on the power scheduling and rate control problem.

3 Algorithm

When solving problem (P), if we already knew the underlying probability distribution for the system states (i.e., π_s, $\forall s \in \mathbf{S}$), the problem would be equivalent to a deterministic convex optimization problem that can easily be solved. However, in practice, we do not have such a priori knowledge. Thus, we need to develop an algorithm that will work even without such a priori knowledge of the underlying probability distribution for the system states. To this end, we consider the dual of problem (P). Since problem (P) is a convex optimization problem, there is no duality gap between problem (P) and its dual and, thus, we can obtain the optimal solution of problem (P) by solving its dual.

We define a Lagrangian function associated with problem (P) as

$$\begin{aligned}
& L(\bar{x}, \bar{P}, \bar{\mu}, \bar{\lambda}) \\
= & \sum_{m\in\mathbf{M}} a_m U_m(x_m) - \sum_{s\in\mathbf{S}} \pi_s \sum_{i,j:(i,j)\in\mathbf{L}} b_{i,j} P_{i,j}^s \\
& + \sum_{i,j:(i,j)\in\mathbf{L}} \mu_{i,j} \Big(\sum_{s\in\mathbf{S}} \pi_s r_{i,j}^s(P_{i,j}^s) - \sum_{k\in\mathbf{M}_{i,j}} x_k\Big) \\
& + \sum_{i\in\mathbf{N}} \lambda_i \Big(P_i^a - \sum_{s\in\mathbf{S}} \pi_s \sum_{j:(i,j)\in\mathbf{L}_i^{out}} P_{i,j}^s\Big) \\
= & \sum_{m\in\mathbf{M}} a_m U_m(x_m) - \sum_{s\in\mathbf{S}} \pi_s \sum_{i\in\mathbf{N}} \sum_{j:(i,j)\in\mathbf{L}_i^{out}} b_{i,j} P_{i,j}^s \\
& + \sum_{s\in\mathbf{S}} \pi_s \sum_{i\in\mathbf{N}} \sum_{j:(i,j)\in\mathbf{L}_i^{out}} \mu_{i,j} r_{i,j}^s(P_{i,j}^s) \\
& - \sum_{m\in\mathbf{M}} \sum_{i,j:(i,j)\in\mathbf{V}_m} \mu_{i,j} x_m \\
& + \sum_{i\in\mathbf{N}} \lambda_i \Big(P_i^a - \sum_{s\in\mathbf{S}} \pi_s \sum_{j:(i,j)\in\mathbf{L}_i^{out}} P_{i,j}^s\Big) \\
= & \sum_{s\in\mathbf{S}} \pi_s \Big\{ \sum_{m\in\mathbf{M}} \Big(a_m U_m(x_m) - \sum_{i,j:(i,j)\in\mathbf{V}_m} \mu_{i,j} x_m\Big) \\
& + \sum_{i\in\mathbf{N}} \sum_{j:(i,j)\in\mathbf{L}_i^{out}} \big(-b_{i,j} P_{i,j}^s + \mu_{i,j} r_{i,j}^s(P_{i,j}^s) - \lambda_i P_{i,j}^s\big) \\
& + \sum_{i\in\mathbf{N}} \lambda_i P_i^a \Big\},
\end{aligned}$$

where $\bar{\mu} = (\mu_{i,j})_{i,j:(i,j)\in\mathbf{L}}$, $\bar{\lambda} = (\lambda_i)_{i\in\mathbf{N}}$, $\bar{P} = (P_{i,j})_{i,j:(i,j)\in\mathbf{L}, s\in\mathbf{S}}$, $\mathbf{L}_i^{out}$ is a set of links that emanate from node i, $\mathbf{M}_{i,j}$ is a set of users that are using link (i,j), and $\mathbf{V}_m$ is a set of links that user m is using. Then, the dual problem is defined as:

$$\text{(D)} \qquad \min_{\bar{\mu}\ge\bar{0},\ \bar{\lambda}\ge\bar{0}} Q(\bar{\mu}, \bar{\lambda}),$$

where

$$Q(\bar{\mu}, \bar{\lambda}) = \max_{\bar{x}\in\mathbf{X},\ \bar{P}\in\mathbf{P}} L(\bar{x}, \bar{P}, \bar{\mu}, \bar{\lambda}), \tag{4}$$

$\mathbf{X} = \{(x_m)_{m\in\mathbf{M}} \mid x_m^{min} \le x_m \le x_m^{max},\ \forall m \in \mathbf{M}\}$, and $\mathbf{P} = \{(\bar{P}_i^s)_{i\in\mathbf{N},\ s\in\mathbf{S}} \mid \bar{P}_i^s \in \mathbf{P}_i^s,\ \forall i \in \mathbf{N}, s \in \mathbf{S}\}$. We first consider the problem in (4) for a given $\bar{\mu}$ and $\bar{\lambda}$. Since $L(\bar{x}, \bar{P}, \bar{\mu}, \bar{\lambda})$ is separable in s, $\bar{x}(\bar{\mu}) = (x_m(\bar{\mu}))_{m\in\mathbf{M}}$ and $\bar{P}(\bar{\mu}, \bar{\lambda}) = (\bar{P}_i^s(\bar{\mu}, \bar{\lambda}))_{i\in\mathbf{N},\ s\in\mathbf{S}}$ solve the problem in (4), if and only if

$$\begin{aligned}
x_m(\bar{\mu}) &= \arg \max_{x_m^{min}\le x_m\le x_m^{max}} \{a_m U_m(x_m) - \\
& \qquad \sum_{i,j:(i,j)\in\mathbf{V}_m} \mu_{i,j} x_m\},\ m \in \mathbf{M}
\end{aligned} \tag{5}$$

and

$$\begin{aligned}
\bar{P}_i^s(\bar{\mu}, \bar{\lambda}) &= \arg \max_{\bar{P}_i^s\in\mathbf{P}_i^s} \{ \sum_{j:(i,j)\in\mathbf{L}_i^{out}} -b_{i,j} P_{i,j}^s \\
& \quad + \mu_{i,j} r_{i,j}^s(P_{i,j}^s) - \lambda_i P_{i,j}^s\} \\
&= \arg \max_{\bar{P}_i^s\in\mathbf{P}_i^s} \{ \sum_{j:(i,j)\in\mathbf{L}_i^{out}} (W \mu_{i,j} \frac{G_{i,j}^s}{n_j^s} \\
& \quad - b_{i,j} - \lambda_i) P_{i,j}^s\},\ i \in \mathbf{N},\ s \in \mathbf{S},
\end{aligned} \tag{6}$$

where (6) is obtained by using (1) and (2). Note that for a given system state s, the above problems are deterministic and we can solve them without knowledge of the underlying probability distribution.

We now solve the dual problem (D). However, to minimize $Q(\bar{\mu}, \bar{\lambda})$, we need knowledge of the underlying probability distribution, which is infeasible to obtain in practice.

To overcome this difficulty, we use a stochastic subgradient method [7, 6] that is defined by the following iterative processes:

$$\mu_{i,j}^{(n+1)} = [\mu_{i,j}^{(n)} - \alpha^{(n)} v_{\mu_{i,j}}^{(n)}]^+, \ \forall i,j : (i,j) \in \mathbf{L} \quad (7)$$

and

$$\lambda_i^{(n+1)} = [\lambda_i^{(n)} - \alpha^{(n)} v_{\lambda_i}^{(n)}]^+, \forall i \in \mathbf{N}, \quad (8)$$

where $[a]^+ = \max\{0,a\}$, and $v_{\mu_{i,j}}^{(n)}$ and $v_{\lambda_i}^{(n)}$ are some random variables. Let the sequences of solutions, $\bar{\mu}^{(0)}, \bar{\mu}^{(1)}, \cdots, \bar{\mu}^{(n)}$ and $\bar{\lambda}^{(0)}, \bar{\lambda}^{(1)}, \cdots, \bar{\lambda}^{(n)}$ be generated by (7) and (8), respectively. Let $v_{\mu_{i,j}}^{(n)}$ and $v_{\lambda_i}^{(n)}$ be chosen such that

$$\begin{aligned} & E\{v_{\mu_{i,j}}^{(n)} \mid \bar{\mu}^{(0)}, \bar{\mu}^{(1)}, \cdots, \bar{\mu}^{(n)}, \bar{\lambda}^{(0)}, \bar{\lambda}^{(1)}, \cdots, \bar{\lambda}^{(n)}\} \\ = \ & \partial_{\mu_{i,j}} Q(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)}) \end{aligned}$$

and

$$\begin{aligned} & E\{v_{\lambda_i}^{(n)} \mid \bar{\mu}^{(0)}, \bar{\mu}^{(1)}, \cdots, \bar{\mu}^{(n)}, \bar{\lambda}^{(0)}, \bar{\lambda}^{(1)}, \cdots, \bar{\lambda}^{(n)}\} \\ = \ & \partial_{\lambda_i} Q(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)}), \end{aligned}$$

respectively, where $E\{v\}$ is the expected value of a random variable v, and $\partial_{\mu_{i,j}} Q(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)})$ and $\partial_{\lambda_i} Q(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)})$ are subgradients of $Q(\bar{\mu}, \bar{\lambda})$ at $\bar{\mu} = \bar{\mu}^{(n)}$ and $\bar{\lambda} = \bar{\lambda}^{(n)}$ with respect to $\mu_{i,j}$ and λ_i, respectively. Then, $v_{\mu_{i,j}}^{(n)}$ and $v_{\lambda_i}^{(n)}$ are called stochastic subgradients of $Q(\bar{\mu}, \bar{\lambda})$ at $\bar{\mu} = \bar{\mu}^{(n)}$ and $\bar{\lambda} = \bar{\lambda}^{(n)}$ with respect to $\mu_{i,j}$ and λ_i, respectively. By using these iterative procedures with a sequence of step sizes that satisfies

$$\alpha^{(n)} \geq 0, \ \sum_{n=0}^{\infty} \alpha^{(n)} = \infty, \text{ and } \sum_{n=0}^{\infty} (\alpha^{(n)})^2 < \infty,$$

dual variables $\bar{\mu}^{(n)}$ and $\bar{\lambda}^{(n)}$ converge to the optimal solutions that solve the dual problem (D) with probability one [7, 6]. To apply this method to solve problem (D), we need to know stochastic subgradients of $Q(\bar{\mu}, \bar{\lambda})$, i.e., $v_{\mu_{i,j}}^{(n)}$ and $v_{\lambda_i}^{(n)}$, and they are obtained by [10, 9]

$$v_{\mu_{i,j}}^{(n)} = r_{i,j}^{s^{(n)}}(P_{i,j}^{s^{(n)}}(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)})) - \sum_{k \in \mathbf{M}_{i,j}} x_k^{(n)}(\bar{\mu}^{(n)}) \quad (9)$$

and

$$v_{\lambda_i}^{(n)} = \sum_{j:(i,j) \in \mathbf{L}_i^{out}} P_{i,j}^{s^{(n)}}(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)}) - P_i^a, \quad (10)$$

where $s^{(n)}$ is a system state at iteration n, and $x_k^{(n)}$ and $\bar{P}_i^{s^{(n)}}(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)}) = (P_{i,j}^{s^{(n)}}(\bar{\mu}^{(n)}, \bar{\lambda}^{(n)}))_{j:(i,j) \in \mathbf{L}_i^{out}}$ are solutions to the problems in (5) and (6), respectively, with $\bar{\mu} = \bar{\mu}^{(n)}$ and $\bar{\lambda} = \bar{\lambda}^{(n)}$. Note that this stochastic subgradient method does not require a priori knowledge of the underlying probability distribution for system states. It only requires the system state at the current iteration, which can be obtained by measuring the channel condition of each link at the current iteration.

Thus far, we have developed an algorithm that solves the dual problem (D) even without a priori knowledge of system states. This algorithm can be implemented in a distributed way. First, each node i allocates power and data rate to each link that emanates from it, i.e., to each link (i,j), $j : (i,j) \in \mathbf{L}_i^{out}$, and updates parameters λ_i and $\mu_{i,j}$, $j : (i,j) \in \mathbf{L}_i^{out}$ based on its local information. In time-slot n, based on $(\mu_{i,j}^{(n)})_{j:(i,j) \in \mathbf{L}_i^{out}}$, $\lambda_i^{(n)}$, and the channel condition of each link (i,j), $j : (i,j) \in \mathbf{L}_i^{out}$, each node i solves the problem in (6) and obtains the power level for each link $(i,j) : j \in \mathbf{L}_i^{out}$ as

$$P_{i,j}^{s^{(n)}} = \begin{cases} P_i^T, & \text{if } j = \arg\max_{k \in \mathbf{L}_i^{out}} \{W \mu_{i,k}^{(n)} \frac{G_{i,k}^{s^{(n)}}}{n_k^{s^{(n)}}} \\ & -b_{i,k} - \lambda_i^{(n)} > 0 \mid W \mu_{i,k}^{(n)} \frac{G_{i,k}^{s^{(n)}}}{n_k^{s^{(n)}}} - \\ & b_{i,k} - \lambda_i^{(n)}\} \\ 0, & \text{otherwise} \end{cases}.$$

The above equation implies that each node transmits to at most one link in a time-slot and its maximum power level is allocated to the selected link. The data rate for the link is obtained by using (2) based on the power allocation. After allocating power and data rate, based on its power consumption and the aggregate data rate of the users that are using each link $(i,j) : j \in \mathbf{L}_i^{out}$ in the current time-slot, each node i updates parameters λ_i and $\mu_{i,j}$, $j : (i,j) \in \mathbf{L}_i^{out}$ for the next time-slot by using (7) - (10). The data rate of each user is determined by the user itself based on its local information. In time-slot n, each user m determines its data rate $x_m^{(n)}$ by solving the problem in (5). To solve the problem, the user requires the sum of $\mu_{i,j}^{(n)}$'s, $i,j : (i,j) \in \mathbf{V}_m$, i.e., the sum of $\mu_{i,j}^{(n)}$'s corresponding to its routing path. It can be obtained by feedback from the nodes that are on its routing path.

4 Numerical Results

In this section, we provide numerical results to illustrate various features of our joint opportunistic power scheduling and rate control scheme. We consider a wireless ad-hoc network in Fig. 1 that consists of six nodes and five users (C_1–C_5). Each node i has maximum transmission power limit of one unit, i.e., $P_i^T = 1$. We model the path gain of link (i,j) $G_{i,j}$ as

$$G_{i,j} = \frac{10^{K_{i,j}}}{d_{i,j}^{\alpha}}, \quad (11)$$

Table 1. Data rate and utility (Data rate/Utility).

a	C_1	C_2	C_3	C_4	C_5	Total
0	1/0	1/0	1/0	1/0	1/0	5/0
0.2	1/0	2.95/1.08	1/0	2.94/1.08	2.86/1.05	10.75/3.21
0.4	1/0	4.76/1.56	1/0	4.82/1.57	4.87/1.58	16.45/4.72
0.6	1/0	5.95/1.78	1.01/0.01	5.94/1.78	5.22/1.65	19.12/5.23
0.8	1/0	6.22/1.83	1.02/0.02	6.31/1.84	4.88/1.58	19.43/5.27
1.0	1/0	6.48/1.87	1.01/0.01	6.49/1.87	4.69/1.55	19.67/5.3

Table 2. Average power consumption.

a	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Total
0	0.14	0.494	0.029	0.029	0.014	0.014	0.72
0.2	0.202	0.494	0.151	0.152	0.014	0.075	1.088
0.4	0.303	0.5	0.351	0.355	0.015	0.174	1.698
0.6	0.402	0.5	0.5	0.5	0.015	0.262	2.179
0.8	0.433	0.5	0.5	0.5	0.015	0.292	2.24
1	0.5	0.5	0.5	0.5	0.5	0.5	3

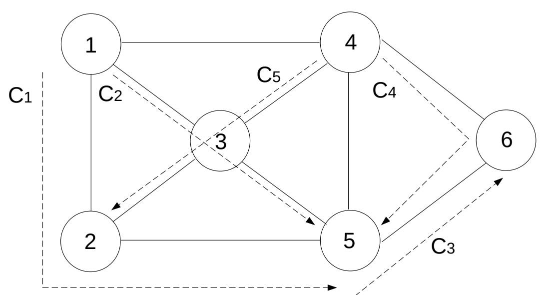

Figure 1. Network model.

where $d_{i,j}$ is the distance from node i to node j, α is a distance loss exponent, and $K_{i,j}$ is a normally distributed random variable with mean 0 and variance σ^2 (dB), which represents shadowing [18]. We set $\sigma = 4$ (dB) and $\alpha = 4$. We assume that each node i has a unit level of background noise, i.e., $n_i = 1$. Each user m has a utility function U_m which is defined as

$$U_m(x_m) = \log(x_m).$$

We first simulate our scheme by varying weight factors a_m and $b_{i,j}$ in (3). By adjusting these weight factors, we can control the trade-off between network performance (total system utility) and power consumption. We set $a_m = a$, $\forall m \in \mathbf{M}$ and $b_{i,j} = 1 - a$, $\forall i, j : (i, j) \in \mathbf{L}$. A larger value of a implies that we put more weight on increasing network performance and less weight on decreasing power consumption. We also set $P_i^a = P_i^T/2 = 0.5, \forall i \in \mathbf{N}$, and $x_m^{min} = 1$ and $x_m^{max} = 10$, $\forall m \in \mathbf{M}$. Hence, each node has a constraint on its average power consumption and each user has constraints on its minimum and maximum data rates. We provide the achieved data rate and utility for each user in Table 1 and the average power consumption for each node in Table 2. When $a = 0$, the objective of our problem becomes to obtain joint power scheduling and rate allocation that minimizes the average total power consumption. Hence, each user is allocated its minimum data rate to minimize power consumption of the network. As the value of a increases, in general, the data rate of each user is also increased providing higher total system utility. This increase in network performance comes by a corresponding increase in power consumption of the network. Hence, as the value of a is increases, the average power consumption of each node also increases. However, this increase is limited by the maximum average power consumption constraint. When $a = 1$, the objective of our problem becomes to obtain joint power scheduling and rate allocation that maximizes the total system utility. Hence, each node consumes its power as much as possible within its maximum average power constraint to maximize system performance.

To show the performance gain of our opportunistic scheme over a non-opportunistic scheme, we now simulate a non-opportunistic scheme, in which the time-varying channel condition of each link is not exploited for resource allocation. In this scheme, each user has a unit data rate and each node allocates power to its links based on the average channel condition of each link such that each link can support the aggregate data rate of the users on that link. To this end, in each time slot, the power allocation $P_{i,j}^{non}$ for each

Table 3. Comparison of the average power consumptions.

Node	1	2	3	4	5	6	Total
Opportunistic	0.14	0.494	0.029	0.029	0.014	0.014	0.72
Non-opportunistic	0.511	0.818	0.204	0.204	0.102	0.102	1.94

Table 4. Comparison of the achieved data rates.

User	C_1	C_2	C_3	C_4	C_5
Opportunistic	1.20	3.58	1.21	3.68	3.13
Non-opportunistic	1	1	1	1	1

link (i, j) is obtained by using (2) as

$$P_{i,j}^{non} = \frac{n_j \sum_{m \in \mathbf{M}_{i,j}} x_m}{WE\{G_{i,j}\}} = \frac{n_j |M_{i,j}|}{WE\{G_{i,j}\}},$$

where $|M_{i,j}|$ is the number of the users that are using link (i, j). Hence, in this scheme, each user is allocated the same data rate as in our previous simulation with $a = 0$. We provide the average power consumption for each node and the total average power consumption of the network in each scheme in Table 3. As shown in Table 3, our opportunistic scheme requires less power from each node than its non-opportunistic counterpart to achieve the same performance.

We now simulate our opportunistic scheme with $x_m^{min} = 1$, $x_m^{max} = 10$, and $a_m = 1$ for each user m, and $b_{i,j} = 0$ for each link (i, j). We further set the maximum average power consumption P_i^a for each node i as the average power consumption of each node in the non-opportunistic scheme in Table 3, i.e., $P_0^a = 0.511$, $P_1^a = 0.818$, and so on. Since we set $a_m = 1$ and $b_{i,j} = 0$, our algorithm maximizes the sum of the utilities of all users without concerning minimizing power consumption. However, the power consumption in each node is controlled by the constraint on its maximum average power consumption, which is the same value as the average power consumption of each node in the non-opportunistic scheme. Hence, this simulation illustrates the performance gain of our scheme over the non-opportunistic scheme when both schemes consume the same amount of power. Table 4 shows the achieved data rate of each user in each scheme and our scheme provides a higher data rate to each user than the non-opportunistic scheme.

5 Conclusion

In wireless networks, the channel condition of the communication link is time-varying and exploiting this property is important in improving system efficiency. In this paper, we have modeled the channel condition as a stochastic process and developed a joint opportunistic power scheduling and rate control algorithm for wireless ad-hoc networks. Our algorithm maximizes system efficiency, which is defined as the weighted sum of the utilities of all users and the average power consumption of all nodes, while satisfying the constraints on the data rate of each user and power consumption of each node. Numerical results show that by using our scheme, i.e., by opportunistically exploiting the time-varying channel condition of each link, we can improve system performance while reducing power consumption at each node in the system.

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